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Fear of Missing Out Mediates the Relationship Between Intolerance of Uncertainty and Problematic Smartphone Use Severity

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Abstract

Despite the widespread use of smartphones, not all users develop problematic use. Understanding the pathways that lead from healthy to Problematic Smartphone Use (PSU) is essential for uncovering underlying mechanisms and informing effective prevention strategies. Building on theoretical models of PSU, this study explores a maladaptive regulatory-focused pathway linking Intolerance of Uncertainty (IU) to PSU through Fear of Missing Out (FoMO) as a mediator. Although previous research has linked IU, FoMO, and PSU in pairs, few studies have examined these constructs simultaneously within a unified explanatory framework. By integrating them into a theoretically grounded mediation model, this study offers a more comprehensive understanding of psychological mechanisms that may underlie PSU. We conducted a cross-sectional online survey with 343 U.S. undergraduate students, recruited through a university research pool in exchange for course credit. Participants completed self-report measures of IU, FoMO, and PSU. Using structural equation modeling, we examined a mediation model incorporating latent variables for IU, FoMO, and PSU, assessing both direct and indirect effects of IU on PSU through FoMO. Results indicated that IU showed a positive association with FoMO, which was further associated with elevated PSU levels. The direct association between IU and PSU was non-significant. These findings support theoretical models positing that personal predispositions, such as IU, contribute to PSU through Internet-related cognitive biases like FoMO. Preventive initiatives should focus on raising awareness about the adverse effects of IU and FoMO on PSU and promoting strategies to effectively manage IU and FoMO, potentially reducing the risk of PSU.

Keywords: intolerance of uncertainty; fear of missing out; problematic smartphone use; smartphone addiction; indirect effects

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Introduction

Smartphones are ubiquitous and versatile, deeply integrated into our daily lives. The number of smartphone users continues to rise with global smartphone mobile network subscriptions nearing 7 billion in 2023 and projected to reach 7.9 billion in 2028[1]. With this widespread adoption, problematic smartphone use (PSU) has become a growing concern (Busch & McCarthy, 2021; Elhai et al., 2017; Nawaz, 2024). Although most people use their devices effectively to fulfill their needs and goals without developing problematic use (Nawaz, 2024), around 20% of users may develop PSU (Kwon et al., 2013; Nahas et al., 2018; Raney et al., 2023). Understanding the pathways leading from healthy use to PSU is crucial for identifying underlying mechanisms and informing prevention efforts (Nawaz, 2024).

PSU is commonly conceptualized within the framework of behavioral addiction, although further evidence, particularly from behavioral and neurobiological studies, is needed to fully validate this conceptualization (Billieux et al., 2015). PSU shares core symptoms with other behavioral addictions, such as Internet addiction, including salience, tolerance, withdrawal, mood modification, loss of control, and relapse, accompanied by functional impairments in daily life (Billieux et al., 2015; Busch & McCarthy, 2021; Elhai et al., 2017). Reflecting this conceptualization, many commonly used PSU measures were developed by adapting elements from the behavioral addiction framework. For example, the widely used Smartphone Addiction Scale-Short Version (SAS-SV; Kwon et al., 2013), adapted from Internet addiction measures, assesses several key features: disruption of daily functioning due to smartphone use; psychological distress when access is restricted; preference for relationships maintained through smartphones over real-life interactions; inability to control smartphone use; and unsuccessful attempts to reduce usage. These features reflect core components of behavioral addiction and have been widely used to characterize PSU.

Systematic reviews of the literature on PSU suggest that its risk factors are multifaceted (Busch & McCarthy, 2021). Consistently, theoretical models of PSU suggest diverse pathways that may lead to PSU. For instance, Billieux et al. (2015) proposed that PSU can arise from the need for excessive reassurance, lack of impulse control, and a strong desire for socialization. The Interaction of Person-Affect-Cognition-Execution (I-PACE) model, a comprehensive framework for understanding Internet use disorders, suggests that a person's core characteristics (P-component in the I-PACE model) shape their responses to internal and external Internet-related cues. These individual responses can trigger a series of affective (A-component) and cognitive (C-component) processes that influence the development of specific problematic Internet use behaviors, with difficulties in inhibitory control intensifying these pathways (Brand et al., 2016; 2019). Building on these models, numerous studies have examined how predisposing factors, such as temperament and psychopathology, lead to PSU through emotional and cognitive biases (Arrivillaga et al., 2023; Elhai et al., 2018; 2019). Adding to the existing literature, the present study aims to investigate a maladaptive regulatory-focused pathway where intolerance of uncertainty (IU; P-component) contributes to fear of missing out (FoMO; C-component), ultimately leading to PSU.

IU is characterized by a dispositional inability to endure aversive responses triggered by a perceived lack of sufficient information (Carleton, 2016). Research has shown that greater IU predicts greater severity of PSU (Korol, 2021; Sang et al., 2024). Regarding potential mechanisms underlying this link, network analysis suggests that the negative affect triggered by perceived uncertainty, which may reflect difficulties in regulating uncertainty-induced aversive emotions related to IU, drives individuals with high IU to engage in coping-motivated smartphone use, thereby facilitating PSU (Liu et al., 2022). Consistent with this regulatory-focused perspective, research has found that IU contributes to PSU through increased non-social smartphone use, indicating that individuals may use smartphones to alleviate negative affect or seek information in the face of uncertainty (Rozgonjuk et al., 2019). Another study found that IU increases anxiety and reduces adaptive coping, which in turn leads to PSU (Qiu et al., 2024). Additionally, Carleton et al. (2019) revealed an increased level of IU from 1999 to 2014, which correlated significantly with enhanced mobile phone and Internet use during the same period. It was suggested that for individuals struggling to regulate distress precipitated by perceived uncertainty, there may be a greater need for reassurance-seeking. Smartphones provide a rapid solution for facilitating access to reassurance, through receiving messaging from friends and loved ones, and receiving likes, views and comments on social media (Elhai, Rozgonjuk, et al., 2020). Thus, smartphones can act as a modern safety cue for those with high IU, leading to a vicious cycle of IU and smartphone use, ultimately elevating the likelihood of developing PSU. Altogether, these findings underscore that individuals with high IU likely use smartphones to mitigate perceived uncertainty and associated distress, highlighting IU as a strong antecedent of PSU.

FoMO is another important antecedent of PSU. FoMO is characterized by a constant concern that others might be having rewarding experiences from which one is absent, leading to a strong desire to stay informed about what others are doing (Przybylski et al., 2013). Research has shown that FoMO not only directly contributes to PSU but can also mediate the relationship between psychopathology (i.e., anxiety, depression) and PSU (Elhai et al., 2019). These findings suggest that individuals experiencing greater levels of anxiety or depression are more likely to experience FoMO, and may consequently use smartphones excessively to mitigate their FoMO. Elhai et al. (2021) further conceptualized FoMO as an Internet-related cognitive bias, where the apprehension of missing out on rewarding experiences resembles the cognitive aspects of anxiety, such as worry. This bias cultivates motivations for and likely triggers maladaptive regulatory behaviors, such as compulsively checking and responding to notifications (also involving reassurance seeking), which can lead to PSU. In addition, individual differences in FoMO have been observed. Younger individuals were found to report higher levels of FoMO, and certain personality traits were implicated: higher neuroticism was significantly associated with greater FoMO, while lower levels of conscientiousness, agreeableness, openness, and extraversion showed weaker associations (Rozgonjuk et al., 2021).

Further, FoMO has been conceptualized as comprising both trait and state components. Trait FoMO reflects a stable, general tendency to worry about missing out on important experiences, whereas state FoMO refers specifically to FoMO experienced in online contexts, such as concerns about missing out on others' social media activities, and is considered less stable and more situation-dependent (Hussain et al., 2024; Wegmann et al., 2017). Both forms of FoMO are associated with problematic social networking site use (PSNSU) and PSU. However, in a model including both trait and state FoMO as predictors of PSU, only state FoMO significantly predicted PSU indirectly via PSNSU, whereas trait FoMO did not show a significant indirect effect (Hussain et al., 2024). This suggests that the online-context-specific nature of state FoMO may make it more relevant in driving PSU.

In sum, FoMO is a construct highly relevant to PSU. The constant need to stay connected and informed, driven by FoMO, may lead individuals to engage in frequent smartphone use to ensure they are not missing out on important updates, thereby reinforcing dependence on smartphones and potentially contributing to PSU (Elhai et al., 2025). Moreover, the observed individual differences in FoMO underscore the importance of considering factors that may influence FoMO when examining its role in the development of PSU. Accounting for such differences may provide a more nuanced understanding of how FoMO contributes to PSU.

Notably, research has shown that individuals with higher levels of IU tend to experience greater FoMO (Alfasi, 2021). There is also indirect evidence supporting the association between IU and FoMO. Individuals with high IU often experience heightened levels of anxiety, depression, and overall life dissatisfaction (Al-Khaz'Aly et al., 2023; McEvoy et al., 2019), all of which contribute significantly to FoMO (Przybylski et al., 2013). Intuitively, IU and FoMO are closely related concepts. FoMO involves an apprehension about missing out on rewarding experiences, which to some extent is driven by uncertainty about what others are doing in one's social network. Individuals with high IU may find it particularly challenging to tolerate uncertainty associated with not knowing about others' activities and the possibility of missing out stemming from this uncertainty, thereby increasing their susceptibility to FoMO. Thus, it is plausible to suggest that IU can intensify the apprehension arising from being uninformed and the desire to stay connected, further contributing to FoMO.

From a theoretical perspective, IU may contribute to PSU through FoMO. According to the I-PACE model, IU represents a stable personal characteristic (P-component) that shapes responses to internal and external Internet cues. FoMO, on the other hand, can be viewed as a cognitive component (C-component; an Internet-related cognitive bias) that mediates the relationship between personal characteristics and Internet use disorders. It has been demonstrated that IU triggers aversive responses and impedes effective self-regulatory processes when faced with uncertainty (Carleton, 2016; Rettie & Daniels, 2021; Sahib et al., 2023). This process leads individuals with high IU to develop various cognitive biases, such as repetitive negative thinking, negative metacognitions about worry, and fear of negative evaluation (Sang et al., 2024; Shihata et al., 2017). FoMO can be seen as one such cognitive bias (Elhai et al., 2019, 2021; Wegmann et al., 2017). Research indicates that individuals with high IU often experience heightened anxiety, worry, and a pervasive need for reassurance (Carleton, 2016; Carleton et al., 2019), which may contribute to FoMO. Consequently, FoMO could further drive individuals to incessantly check for updates or notifications on their smartphones, leading to PSU. Additionally, in alignment with the pathway model of PSU (Billieux et al., 2015), the hypothesized pathway leading from IU and FoMO to PSU represents an example of the excessive reassurance pathway, such that individuals with high IU may use their smartphones as a safety cue to cope with uncertainty. Furthermore, those with high IU are also prone to experience heightened FoMO, which drives them to habitually engage in smartphone use to stay informed, ultimately resulting in PSU.

The current study builds on and extends prior work by empirically testing a novel, theoretically grounded pathway from IU to PSU, mediated by FoMO. While previous studies have independently demonstrated associations between IU and PSU (e.g., Korol, 2021; Liu et al., 2022), FoMO and PSU (Elhai et al., 2019), and, to a lesser extent, IU and FoMO (Alfasi, 2021), these constructs have rarely been examined together within an integrated explanatory model. To our knowledge, this is among the first of studies to empirically test whether FoMO functions as a cognitive mediator between IU and PSU, a mechanism suggested by theoretical frameworks such as the I-PACE model (Brand et al., 2016) and the pathway model of PSU (Billieux et al., 2015), but not yet directly assessed. Despite its cross-sectional design, the study has both theoretical and practical relevance. Theoretically, it may advance the I-PACE model by suggesting a potential cognitive-affective mechanism (FoMO) through which a personal trait (IU) could be linked to PSU. It may also help refine the pathway model of PSU (Billieux et al., 2015) by providing empirical support for the excessive reassurance pathway, whereby individuals with high IU might experience greater distress about uncertainty in online contexts, potentially linking to increased FoMO and frequent smartphone checking as a means of reassurance. Practically, by exploring the IU–FoMO–PSU associations, the study may help identify potential targets for early screening and intervention. For instance, individuals with elevated IU and FoMO scores may be at higher risk for PSU. Intervention strategies aimed at enhancing tolerance for uncertainty might help reduce PSU risk by reducing FoMO and the associated urge to stay constantly updated on rewarding online experiences. Based on the above reviewed literature, we have the following hypotheses:

H1: IU and FoMO are positively correlated.

H2: FoMO is linked to greater PSU severity.

H3: FoMO mediates the association between IU and PSU severity.

Methods

Participants

The current sample consisted of 343 participants drawn from a larger survey investigating pathways leading to PSU and gaming. Participants were undergraduate students at a mid-sized Midwestern U.S. university who participated in exchange for psychology course research points through the department's research pool. Participants signed up for this study via the university's Sona Systems web portal, and 379 provided informed consent. The survey took approximately 18 minutes to complete on average and was conducted between September 2020 and April 2021. Participants were excluded for duplicate survey entries (n = 11), answering only a few items (n = 6), not owning a smartphone (n = 4), or responding carelessly (n = 15; identified as providing more than 18 identical responses consecutively), resulting in a final sample of 343 participants. The study procedure received approval from the last author's university Institutional Review Board. The mean age of participants was 19.33 years (SD = 2.50). Of these, 64.7% (n = 222) self-identified as female, and 78.7% (n = 270) identified as white. Participants were mostly employed part-time (50.1%, n = 172) or unemployed (42.6%, n = 146).

Measures

The following measures were administered as part of the larger protocol described above. Measures were administered online in a web survey, in English.

Intolerance of Uncertainty Scale (IUS)

The 12-item abbreviated version of the IUS was used in the current study (Carleton et al., 2007). Participants indicated on a 5-point Likert scale ranging from 1 (*not at all characteristic of me*) to 5 (*entirely characteristic of me*) the extent to which each description of cognitive, emotional, and behavioral responses to perceived uncertainty characterized them. The scale has demonstrated good psychometric properties (Carleton et al., 2007) and Cronbach's alpha value of .92 in the current sample.

Fear of Missing Out (FoMO) Scale

The FoMO scale contains 10 items assessing concerns about others having rewarding experiences from which one is absent (Przybylski et al., 2013). Participants indicated how true each item was of their general experiences on a Likert scale ranging from 1 (*not at all true of me*) to 5 (*extremely true of me*). The scale has demonstrated adequate psychometric properties (Przybylski et al., 2013) and Cronbach's alpha value of .89 in the current sample.

Smartphone Addiction Scale-Short Version (SAS-SV)

The SAS-SV is a 10-item scale assessing aspects of problematic smartphone use, including daily-life disturbance, withdrawal, cyberspace-oriented relationship, overuse, and tolerance (Kwon et al., 2013). Each item was rated on a 6-point scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The SAS-SV demonstrated sound psychometric properties (Kwon et al., 2013). In the current sample, it has a Cronbach's alpha value of .86.

Data Analysis

Data preprocessing was conducted in R 4.2.0 (R Core Team, 2022) using the careless package (Yentes & Wilhelm, 2023) to detect inattentive responses and *dplyr* (Wickham et al., 2023) for data cleaning. Missing data patterns for scales assessing PSU, FoMO, and IU were examined using *naniar* (Tierney et al., 2024); Little's MCAR test indicated data were missing completely at random, supporting the use of expectation-maximization for imputation via the mice package (van Buuren et al., 2023). For each scale, missing items were imputed when fewer than 50% of items were missing; total scores were then computed from the imputed data. For participants missing fewer than half of the total scale scores, missing total scores were also imputed. Actual missingness was minimal: 11 participants (3.2%) had 10% missingness on SAS; 13 (3.8%) had 10–20% missingness on FoMO; 13 (3.8%) had 8.3% missingness on IUS; and one participant with 100% missingness on the IUS was excluded based on the 50% missingness criterion. These low levels of missingness mitigate concerns about bias from imputation.

Descriptive statistics were next calculated. Zero-order bivariate correlations between continuous variables were performed for the full sample, as well as separately for the female and male samples. ANOVA was used to test for sex differences in IU, FoMO, and PSU. To control for multiple comparisons, *p*-values from the correlation analyses were adjusted using the Bonferroni method within each subgroup (full, female, male); *p*-values from the three ANOVAs were adjusted separately, also using the Bonferroni method.

Confirmatory factor analysis (CFA) and structural equation modelling (SEM) were performed using Mplus 8.7 (Muthén & Muthén, 2017). Item responses were treated as ordinal (thus requiring a polychoric covariance matrix and probit factor loadings), and weighted least square parameter estimates (WLSMV) were used. One-factor CFAs were computed for the IUS, FoMO scale, and SAS-SV. For the FoMO scale, residual error covariances between items 1 and 2, and between items 7 and 9, were added post hoc based on large modification indices (MI = 399.85 and 205.10, respectively) and high item-level correlations (r = .86 and r = .73), supported by semantic overlap in item content (Casale & Fioravanti, 2020; Elhai et al., 2025; Ng & Fam, 2024). The incremental improvement in model fit associated with these adjustments is detailed in Appendix Table A1.

Using SEM, we examined a model where IU has a direct effect on FoMO, which further leads to PSU; the direct effect of IU on PSU was also included. To estimate the indirect effect of IU on PSU through FoMO, we used the Delta method with 1,000 bootstrap draws requested to adjust the estimation of standard errors and to calculate 95% confidence intervals (CIs). Model fit was decided according to standard conventions: CFI/TLI values of .95 or .90, SRMR values less than .05 or .08, and RMSEA values less than .06 or .08 indicate good or acceptable fit (Hu & Bentler, 1999; Marsh et al., 2004). Notably, the current study adopted a cross-sectional design and cannot establish temporal precedence between variables. The mediation model was used to examine whether the pattern of associations among variables is consistent with a potential explanatory pathway.

Results

Descriptive Statistics and Preliminary Analyses

The descriptive statistics and correlations of the continuous variables are presented in Table 1. Skewness and kurtosis values for IU, FoMO, and PSU were within acceptable ranges (±1). In contrast, the age variable showed high positive skewness and kurtosis, likely due to the sample being composed primarily of undergraduate students clustered around age 19, with a small number of older participants over age 30. IU and FoMO, as well as FoMO and PSU, were positively corrected with each other with large effect sizes; IU and PSU were positively correlated with a medium effect size. Age was not significantly correlated with these study variables. The correlational pattern between these variables remained consistent across female and male samples (Table 1). According to the ANOVA results, females reported greater IU; $F(1,341) = 6.94$, $p = .009$, adjusted $p = .026$, Partial $\eta^2 = .02$, FoMO; $F(1,341) = 7.65$, $p = .006$, adjusted $p = .018$, Partial $\eta^2 = .02$, and PSU; $F(1,341) = 23.95$, $p < .001$, adjusted $p < .001$, Partial $\eta^2 = .07$, compared to males.

Table 1. *Descriptive Statistics and Correlations of Study Variables.*

	N	Mean	*SD*	Skewness	Kurtosis	1	2	3
Full Sample								
1. Intolerance of Uncertainty	343	29.95	10.47	0.34	–0.54			
2. Fear of Missing Out	343	22.68	8.43	0.55	–0.30	0.61*		
3. Problematic Smartphone Use	343	26.72	9.47	0.48	0.03	0.39*	0.58*	
4. Age	343	19.33	2.50	5.02	43.07	–0.04	–0.12	0.00
Males								
1. Intolerance of Uncertainty	121	27.95	9.83	0.40	–0.48			
2. Fear of Missing Out	121	20.99	7.55	0.51	–0.39	0.60*		
3. Problematic Smartphone Use	121	23.44	8.64	0.71	0.75	0.36*	0.58*	
4. Age	121	19.66	2.22	0.72	13.34	0.04	–0.04	0.09
Females								
1. Intolerance of Uncertainty	222	31.04	10.66	0.28	–0.58			
2. Fear of Missing Out	222	23.60	8.75	0.50	–0.41	0.60*		
3. Problematic Smartphone Use	222	28.51	9.45	0.38	–0.09	0.37*	0.57*	
4. Age	222	19.14	2.64	6.52	52.98	–0.05	–0.13	0.00

Note. *adjusted $p < .001$.

Confirmatory Factor Analysis

Model fit indices of the CFAs are presented in Table 2. All fit indices, except for RMSEA, indicated acceptable to good fit for the one-factor models of the IUS (CFI = .956, TLI = .946, RMSEA = .115, and SRMR = .048), FoMO scale (CFI = .982, TLI = .976, RMSEA = .106, and SRMR = .044), and SAS-SV (CFI = .950, TLI = .935, RMSEA = .106, and SRMR = .042). RMSEA's poor fit is not surprising, as RMSEA has been found to overestimate model misfit using ordinal indicators, while SRMR may more accurately assess model fit (Shi et al., 2019). Thus, these one-factor models can be deemed to have acceptable fit.

Structural Equation Modeling

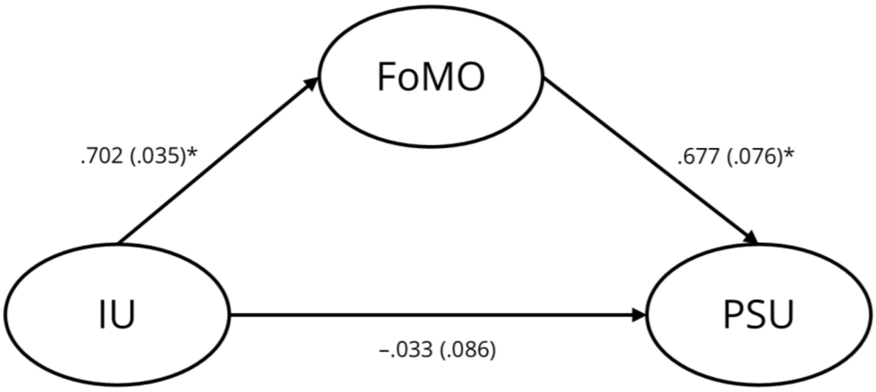
Model fit indices of the structural models indicated good fit (CFI = .957, TLI = .953, RMSEA = .059, and SRMR = .056; see Table 2). The standardized direct effects are presented in Figure 1. The results showed that IU was significantly and positively associated with FoMO (H1), which in turn was associated with greater PSU (H2); the direct effect of IU on PSU was not significant; Estimate = –.033, $SE = .086$, $p = .698$, 95% CI [–.197, .141]. However, the standardized indirect effect of IU on PSU through FoMO was significant (H3), Estimate = .475, $SE = .064$, $p < .001$, 95% CI [.363, .604]. Given the observed sex disparities in IU, FoMO, and PSU severity, we also examined a structural model controlling for the potential influence of sex. Including sex as a covariate did not change the findings (Appendix Table B1).

Table 2. *Model Fit Indices of Measurement and Structural Models.*

Models	WLSMV χ^2	*df*	RMSEA	RMSEA 90% CI	CFI	TLI	SRMR
Measurement model							
IU	298.997*	54	.115	[.103, .128]	.956	.946	.048
FoMO	160.435*	33	.106	[.090, .123]	.982	.976	.044
PSU	168.691*	35	.106	[.090, .122]	.950	.935	.042
Structural model							
IU→FoMO→PSU	1001.206*	459	.059	[.054, .064]	.957	.953	.056

Note. $^{*}p < .001$. Residual error covariances between items 1 and 2 as well as items 7 and 9 of the FoMO scale were correlated. IU = Intolerance of Uncertainty; FoMO = Fear of Missing Out; PSU = Problematic Smartphone Use.

Figure 1. *FoMO Mediates the Association Between IU and PSU.*



Note. $^{*}p < .001$. IU = Intolerance of Uncertainty; FoMO = Fear of Missing Out; PSU = Problematic Smartphone Use. Circles represent latent variables. The scale item loadings are not shown in order to reduce visual clutter but can be requested from the first author. Standardized direct path coefficients are displayed, with standard errors in parentheses. The indirect path coefficients are presented in text within the results section.

Discussion

This study builds on existing evidence by testing an explanatory pathway from IU to PSU via FoMO. Consistent with our hypotheses, IU, FoMO, and PSU were significantly and positively correlated. More importantly, IU was significantly associated with higher levels of FoMO, which in turn was linked to greater PSU. Notably, the direct effect of IU on PSU was not significant, highlighting the crucial mediating role of FoMO in this relationship.

Our findings indicate that individuals with high IU are more likely to experience greater FoMO, consistent with prior research (Alfasi, 2021). This finding suggests that the feeling of being uninformed and a possibility of missing out constitute an uncertain situation, which could be particularly distressing for individuals with high IU. In addition, the strong association between FoMO and PSU observed in this study corroborates existing literature identifying FoMO as a significant predictor of PSU (Elhai et al., 2019; Elhai, Gallinari, et al., 2020), suggesting that FoMO may act as a cognitive and emotional trigger for PSU. We also observed a significant bivariate correlation between IU and PSU, consistent with prior research demonstrating that higher IU was associated with elevated risk of PSU (Carleton et al., 2019; Korol, 2021). Individuals with high IU struggle to tolerate uncertainty and often engage in maladaptive regulatory strategies to manage the resulting distress (Rettie & Daniels, 2021). Smartphones, being versatile tools that provide easy access to information, connection, and entertainment, become an immediate means to alleviate uncertainty-related distress. However, relying on smartphones to cope with this distress may inadvertently reinforce overuse patterns, linking to elevated risk of PSU among individuals with high IU (Carleton et al., 2019).

Beyond identifying these bivariate associations, our study contributes to the existing literature by suggesting that FoMO may play a key mediating role in the association between IU and PSU. The magnitude of the indirect effect was substantial; notably, after accounting for this indirect pathway, the direct association between IU and PSU was no longer statistically significant. This pattern of results indicates that the link between IU and PSU may be largely attributable to their shared association with FoMO. In today's digital environment, smartphones provide constant access to information and facilitate connection across broad social networks. However, this convenience may also heighten perceived opportunities for missing out on personally relevant content, creating a context that is both pervasive and inherently uncertain. Individuals with high IU may struggle to tolerate this form of uncertainty and the distress it elicits, which may be associated with heightened experiences of FoMO. In turn, elevated FoMO may link to increased urges to stay updated and connected, reflected in smartphone use behaviors such as compulsive checking, preoccupation with smartphone use, and an urge to respond to notifications. These behaviors may, in turn, be associated with higher levels of PSU.

This finding provides empirical support for the I-PACE model (Brand et al., 2016, 2019). According to this model, IU represents a stable personal characteristic (P-component) that influences responses to internal and external Internet cues, leading to Internet-related cognitive biases like FoMO (C-component; Elhai et al., 2019, 2021). This cognitive bias, in turn, promotes excessive smartphone use. Additionally, our findings refine the pathway model of PSU by demonstrating an excessive reassurance pathway, in which low tolerance for uncertainty is associated with increased FoMO and a heightened urge to use smartphones as a means of seeking reassurance (Billieux et al., 2015).

Our study found significant sex differences in PSU severity, with females reporting higher levels than males. Additionally, we observed notable sex differences in IU and FoMO, suggesting that females may be more susceptible to these constructs. Females are generally more vulnerable to anxiety and depression, and IU has been identified as a transdiagnostic risk factor for both conditions (Carleton, 2016; Kessler, 2003; McLean et al., 2011). Elevated IU among females may therefore reflect a broader affective vulnerability. On the other hand, prior research suggests that females tend to place greater importance on maintaining positive social relationships and are more sensitive to social disconnection (Lambert & Hopwood, 2016; Yang & Girgus, 2019). This heightened social sensitivity may contribute to stronger experiences of FoMO. In addition to this, a study on gender differences in PSU risk factors found that higher PSU in males was linked to gaming use, whereas in females it was associated with multimedia consumption (e.g., watching videos, listening to music) and social networking (Chen et al., 2017). These patterns suggest that females' higher FoMO and greater emphasis on social interaction may underlie their higher PSU. Nevertheless, while prior studies have reported similar gender differences, findings remain mixed. Thus, the present results should be interpreted with caution, particularly given that our sample included more female than male undergraduate students (approximately 60% female). Despite these differences, our structural model demonstrated that the mediation effect of IU on PSU through FoMO did not change after controlling for sex. This indicates that the IU-FoMO-PSU pathway likely operates similarly across sex, suggesting that while there are sex differences in the levels of IU, FoMO, and PSU, the processes linking these constructs may not be sex-sensitive.

This finding regarding the IU-FoMO-PSU pathway carries important practical implications for the prevention and intervention of PSU. Specifically, individuals high in IU and FoMO may be at increased risk for developing PSU, and screening for IU and FoMO may help identify individuals who are vulnerable. Moreover, given the roles of IU and FoMO in PSU, educational programs could aim to raise awareness about their impact on smartphone use. For example, schools and universities could hold workshops to teach students about managing uncertainty and promoting healthy smartphone habits, such as encouraging periods without checking smartphones to reduce the urge to stay constantly informed and connected. The pros and cons of smartphone bans in schools could be explored (Montag & Elhai, 2023).

Additionally, interventions for PSU could also focus on enhancing tolerance for uncertainty. For instance, mindfulness-based approaches that promote awareness and acceptance of uncertainty might mitigate IU and its associations with FoMO and PSU (Korol, 2021). Furthermore, cognitive behavioral therapy targeting IU (CBT-IU) effectively reduces IU (Hebert & Dugas, 2019; Zemestani et al., 2021). Given the strong associations among IU, FoMO, and PSU, integrating CBT-IU as a module into interventions targeting PSU could provide a more comprehensive approach, potentially reducing FoMO-related urges to stay constantly connected and the risk of developing PSU.

The current findings should be considered in light of several limitations. First, the sample consisted predominantly of young, self-identified white college students, which may limit the generalizability of findings to other populations and cultures. Second, the cross-sectional design of the study precludes conclusions about temporal relationships between IU, FoMO, and PSU. Future studies should include more diverse samples to improve generalizability and employ longitudinal designs to clarify causal relationships. Third, the study relied on self-reported measures of PSU, reflecting subjective experiences of smartphone use. Future studies could combine objective measures, such as actual smartphone use time, to assess PSU more accurately (Rozgonjuk et al., 2018). Fourth, given that our sample was predominantly female (64.7%), the observed sex differences in IU, FoMO, and

PSU should be interpreted with caution. Unequal group sizes may have affected the stability of the ANOVA results. However, supplementary analyses using Welch's ANOVA (Appendix Table C1), which is robust to unequal variances and sample sizes, yielded similar results, suggesting that the observed sex differences are likely to be reliable in this sample. Still, the imbalanced gender composition may limit the generalizability of these findings. Future studies should aim for more gender-balanced samples to further validate these effects at the population level.

Notwithstanding these limitations, this study elucidates a maladaptive regulatory-focused pathway from IU to PSU through FoMO. These findings contribute to the theoretical understanding of PSU, supporting our hypotheses derived from the I-PACE model that FoMO represents a crucial Internet-related cognitive bias linking the personal disposition of IU to the consequence of PSU. Our findings also have practical implications for developing screening, educational programs, and targeted interventions. By addressing IU and FoMO, we can better manage and prevent PSU, promoting healthier interactions with smartphones.

Footnote

[1] Statista. (2024, June 25). *Number of smartphone mobile network subscriptions worldwide from 2016 to 2023, with forecasts from 2023 to 2028.* https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

Conflict of Interest

The authors do not have any conflicts of interest to report. For reasons of transparency, Jon Elhai notes that he receives royalties for several books published on posttraumatic stress disorder (PTSD); is a paid, full-time faculty member at University of Toledo; occasionally serves as a paid, expert witness on PTSD legal cases; and recently received grant research funding from the U.S. National Institutes of Health.

Use of AI Services

The authors used generative AI (ChatGPT-4, OpenAI Inc., https://openai.com/) to enhance the readability and language of this article. Following the use of the tool, the authors carefully reviewed and edited the content to ensure its accuracy and quality, and they take full responsibility for the final published material.

Authors' Contribution

Nisha Yao: conceptualization, methodology, formal analysis, writing—original draft, writing—review and editing. **Caleb J. Hallauer**: conceptualization, investigation, writing—review and editing. **Elyse F. Hutcheson**: conceptualization, investigation, writing—review and editing. **Jon D. Elhai**: conceptualization, data curation, investigation, methodology, supervision, writing—review and editing.

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Data statement

Data will be made available on request.

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Appendices

Appendix A

Table A1. *Model Fit Indices of the FoMO Scale.*

Full Sample	χ^2	*df*	RMSEA	RMSEA 90% CI	CFI	TLI	SRMR
FoMO	690.504*	35	.234	[.219, .249]	.908	0.882	.099
FoMO R1	344.339*	34	.163	[.148, .179]	.957	0.943	.060
FoMO R2	160.435*	33	.106	[.090, .123]	.982	0.976	.044

Note. FoMO: One-factor model without residual covariances; FoMO R1: One-factor model with residual covariance added between items 1 and 2; FoMO R2: One-factor model with residual covariances added between items 1 and 2, and between items 7 and 9. The modification indices for the residual covariances between items 1 and 2 and items 7 and 9 were 399.850 and 205.098, respectively.

Appendix B

Table B1. *FoMO Mediates the Association Between IU and PSU With Sex as a Covariate.*

	Estimate	*SE*	Est./*SE*	*p*-value	95% CI
Direct effect					
IU→PSU	−.046	.086	−0.531	.595	[−.214, .122]
IU→FoMO	.691	.037	18.887	< .001	[.614, .758]
FoMO→PSU	.656	.076	8.601	< .001	[.511, .807]
The influence of Sex					
Sex→IU	.153	.053	2.886	.004	[.048, .254]
Sex→FoMO	.061	.045	1.354	.176	[−.030, .144]
Sex→PSU	.176	.051	3.413	.001	[.072, .281]
Indirect effect					
IU→FOMO→PSU	.453	.063	7.140	< .001	[.337, .583]

Note. IU = Intolerance of Uncertainty, FoMO = Fear of Missing Out, PSU = Problematic Smartphone Use. This model has good fit: χ^2 = 1033.690*, *df* = 488, RMSEA [90% CI] = .057 [.052, .062], CFI = .956, TLI = .953, SRMR = .058. Standardized coefficients are presented.

Appendix C

Table C1. *Welch's ANOVA Examining Sex Differences.*

		Statistic[a]	*df*1	*df*2	Sig.
Problematic Smartphone Use	Welch	25.24	1.00	266.04	<.001
Fear of Missing Out	Welch	8.33	1.00	278.69	.004
Intolerance of Uncertainty	Welch	7.29	1.00	264.34	.007

Note. a. Asymptotically F distributed.

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